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Procedia Computer Science 9 (2012) 1533 – 1542
Procedia Computer Science

International Conference on Computational Science, ICCS 2012

Multi–agent environment for modelling and analysing market strategies

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Abstract

Our goal was to develop an environment which will make it possible to model and optimise supply chains and company behaviours, as well as to test the influence of applying different decision algorithms. The system consists of a set of companies which cooperate and compete with one another by offering and buying products and negotiating their conditions of transactions. Throughout the presented work we focused on the realisation of the parts of the strategic planner module. Producers tend to maximise profits, among other ways, by modifying the margin of offered products.

The main aim of the applied decision algorithm is to have a feature of adapting to a given situation: to select the best model of the simulation world and to choose the most adequate actions in the given situations. The first aspect is addressed by the use of an adaptive algorithm which chooses the best demand prediction algorithm in a given situation. The second aspect is addressed by the clustering technique which identifies the similar situations on the market as one possible state and assigns with it the most profitable action.

Keywords: multi–agent systems, company modelling, clustering, prediction

1. Introduction

The problem of building a beneficial supply chain of management is nowadays of significant importance.

A supply chain [1] is made up of enterprises (suppliers, focal company, customer) linked together by flows of products, services, information and financial means, which may include production.

As long as useful decisions concerning the setting of market strategies and choice of suppliers and clients are performed by humans, the design of an automatic model of these activities still may potentially offer numerous advantages.

Firstly, there are domains, where the automatic setting of the supply chain and market strategies could be useful, especially in cases of activities concerning virtual goods and services in the Internet, where the response time is an important factor.

Secondly, a development of a system where the setting of supply chains is automatic may make it possible to analyse the behaviour of different market settings and to evaluate strategies of activities.

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doi:10.1016/j.procs.2012.04.168

Our goal was to develop an environment which will make it possible to model and optimise supply chains and company behaviours, as well as to test the influence of the application of different decision algorithms.

The way of achieving it was to apply the decision algorithm with features of adapting to a given situation, to select the best model of the simulation world and to choose the most adequate actions in the given situations. We particularly focused on the problems of the choice of the best prediction of demand for products for the given market conditions and on the choice of the best price margin to win the competition on the market.

The first aspect is addressed by the use of an adaptive algorithm which chooses the best demand prediction algorithm in a given situation.

The important element of the enterprise decision strategy is to guarantee the best level of the stocks, which depends, to a large degree, on the predicted values of orders for the next n simulation steps. The nearer the predicted value is to the real value, the more precisely the warehouse is able to plan deliveries, and is able, in effect, to guarantee that at the end of each step of the simulation only the minimum amount of goods (safety buffer) remains in the warehouse. Incorrect predictions of demand (inflatedness of demand) increases storage costs and an underestimation may cause a lack of components in the warehouse and to subsequent production standstills.

The second aspect is addressed either by the predefined (according to experiences) set of rules or by the clustering technique which identifies the similar situations on the market as one possible state and assigns with it the most profitable action.

2. Related research and useful information

The multi–agent approach is often used for modelling and the optimisation of supply chains. In [2] a concept of a multi–agent environment is presented which consists of different components necessary for the composition of supply–chains, and may be used for analysis of the results of the choice of strategies of company activities. In [3] an overview is given for different problems associated with supply chains which were solved with the use of agents as well as a classification of methods used by agents.

An important aspect of the decision making of agents in supply chains is their way of leading negotiations and the choice of negotiation strategies. In [4] an overview of methods of negotiation modelling (based on game theory, heuristics, argumentation) is given while a classification of negotiation schemas concerning the electronic markets may be found in [5].

Another important question associated with the modern supply chains is their feature associated with the adaptation to the given situation. The analysis of robust or flexible solutions for selected strategies of behaviour is done in [6].

One of the most important elements of adequate decision making is the use of suitable prediction techniques. In [7] the use of prediction by agents, which participate in the tournament of agents building the most economic supply chains – Trading Agent Competition (TAC) [8], is described. For the analysis of the current situation and prediction of future states, techniques of data mining and machine learning are used. For example in [9] association rules, clustering and decision trees are used, and in [10] – Markov correction prediction process and Gausian mixture models are applied.

In our opinion, the main difference between models of the companies and market used by TAC and our model is that, we take into consideration different kinds of contracts (short–term and long–term) in the model.

3. System model

The goal of the work was to design and implement an environment which makes it possible to model different states of the market and to analyse results of the different strategies used by companies on the market.

3.1. Market environment

The market environment consists of the following types of agents: companies, clients and negotiators. Based on input components obtained from other companies–suppliers, the company manufactures final products and delivers them to customers or other companies. The customers declare demands for final products, which leads to assigning contracts with appropriate companies. Contracts are described by the following parameters: the kind of product, number of entities, the price and the time of delivery (usually the shorter time of delivery causes the higher expected and accepted price).

The task of the negotiators is to gather offers of accepted contracts submitted by companies and customers, coupling contracts that fit together and to determine the conditions acceptable for the parties concerned. The separate realisation of the module which represents negotiators that resolve the negotiations between agents makes it possible to change the negotiation model relatively easily, without the necessity of changing remaining decision elements.

In the framework of the works done so far, two different negotiation models of the market subjects were implemented. In the current work, a model for determining price and assigning the partners, based on laws of supply and demand, is used. In [11], another model which takes into consideration the market strength of the given parties is used.

3.2. Model of agent–company

The main subject of the research having the most complex decision elements is the agent representing a company. Its knowledge consists of: (i) quantities of sold elements of the given product in the previous and current simulation steps and a global demand for a given product in the previous and current steps as well as (ii) the level of the current stocks and estimated time of delivery of the product to the client.

The activities of the company are handled by the following behaviours, which group together logically linked actions: (i) participation in the negotiation for selling products; (ii) production and sending sold products to costumers; (iii) optimisation of the production strategy and update of the delivered offer; (iv) sending information about the readiness to pass subsequent steps of the simulation; (v) receiving information about the start of a new step in the simulation.

The agent company consists of the following functional modules (Fig. 1):

- a buyer – responsible for buying components for production,
- a seller – responsible for selling final products and determination conditions of selling,
- a warehouse manager – responsible for determination needs of buying to fulfil the stocks levels and to bear stock maintenance costs,
- a production module – produces final products from input components,
- a strategy manager – responsible for choice of decision strategies and configuration of activities of other modules.

3.3. Strategic manager module – version I

The goal of the work is to identify the best possible strategies of activities of the company for the given conditions. To achieve this goal, we have so far applied techniques of reinforcement learning (such as q–learning algorithm [12]) or different demand level prediction algorithms, rule based and clustering algorithm (last three presented in this paper).

The StrategyManager ($StratMan$) module may be described as follows:

$$StratMan = (conds, preds, strats) \tag{1}$$

where conditions $conds$ represent the current state of the company and its environment, $preds$ represent the predicted evaluation of elements describing conditions and $strats$ represent possible decision activities.

Condition $conds$ consists of the following elements:

- a state of the company – financial means, established contracts and conditions;
- customer behaviour – described by a character of the demand for final products and requirements concerning the prices and the delivery time;
- competitor behaviour – the percent of shares of the market owned by the company;

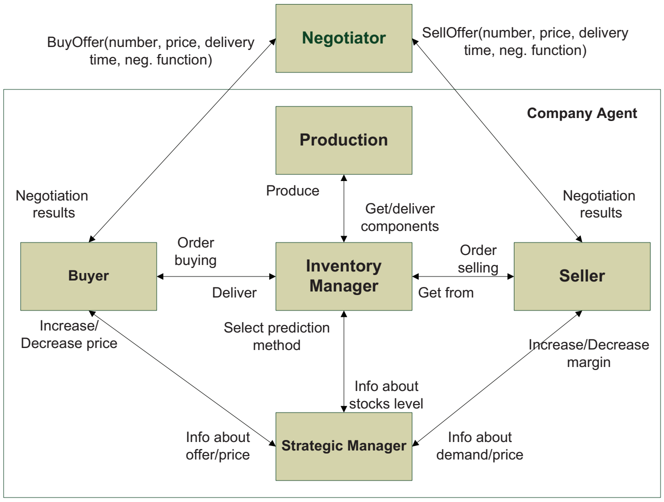

Figure 1: Organisation of the agent company

- supplier behaviour – concerns the supply of components, it is possible to distinguish not sufficient, sufficient and above sufficient level of component supply;
- choice of the current margins for the given products.

The strategical decisions may concern the choice of the storage management strategy (for example ATO, MTO or the increase/decrease of the stock level), level of the margin of profit and used prediction techniques.

In this paper we are focusing on the analysis of the influence of the level of the margin for the final product and the choice of the prediction method of the customer demand. The strategy manager module should select the proper actions to be executed and their configurations.

3.4. Strategic manager module – version II

Decisions concerning actions and their configurations selected by the decision module of the company. The decision module is represented as follows:

$$Dec = (SEM, SMS, MS, SS, ESS, Eval, s, \phi, \theta) \tag{2}$$

where:

- SEM – vector of values of the measures evaluating the state of the company,
- SMS – set of market situations and criterions identifying given situations taking values of measures of state of the company into consideration,
- MS – current market situation of the company,
- SS – set of behaviour strategies with values of decision attributes which configure actions, assigned to given strategies,
- ESS – evaluation of strategy usefulness in the given market situation matrix,
- $Eval$ – function to evaluate usefulness of the strategy in the given market situations $Eval$: $MS \times SS \rightarrow ESS$,
- s – behaviour strategy currently selected from the SS set,

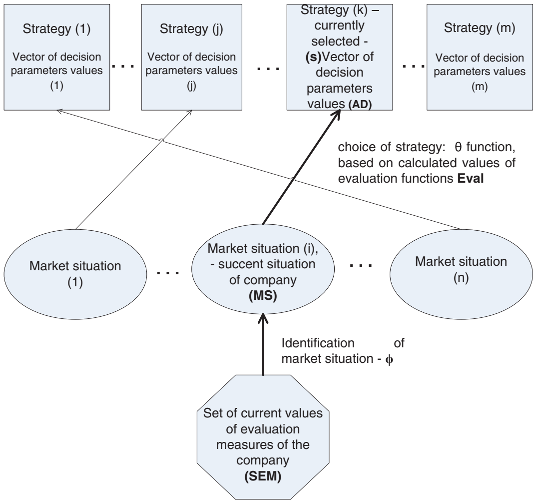

Figure 2: Concept of decision module functioning

- ϕ – function to identify the market situation $\phi : SEM \times SM \rightarrow MS$,
- θ – function to evaluate the behaviour strategy: $\theta : MS \times ESS \rightarrow s$

A concept of module functioning is shown in Fig. 2. Identification of the market situation (MS) is done based on the state of the enterprise and its knowledge of the market (resulting from history and prediction). Values of the description of the situation measures which are described below (SMS) are computed. They make the foundation of the current market situation MS. For given market situations, evaluation of results of appropriate strategies performance from the set SS is done; these evaluations are described by the value increase of the appropriate versions of the goal function after the considered number of steps. On the basis of these values the choice of the most appropriate strategy for a given enterprise is made.

Situation identification. To evaluate the situation of an enterprise, the following measures (SMS) describing the current situation are taken into account:

- Measures characterising the components purchase state (describing the course of action for certain simulation steps):
  - the contracted time of delivery of the i-th copy of the j-th component ordered in step t;
  - the price of the i-th copy of the j-th component ordered in step t, settled by the contract;
  - the number of the delay rounds of the j-th component ordered in step t;
  - the percentage of type j components ordered by an enterprise in the whole demand for the component in step t for the considered market;
  - the percentage of type j components received in the whole demand for the component in step t for the considered market;
- Measures characterising the state of currently possessed resources:
  - the number of possessed copies of components of j type in step t;
  - for how many steps the number of possessed j-type components is sufficient, if they are being sold according to the sale level of the former rounds, taking into consideration enterprise production abilities; evaluations using different methods of demand prediction are possible;

  - for how many steps the number of possessed j-type components is sufficient, if they are being sold in numbers covering the whole demand;

- Measures characterising the final state of product sales:
  - the percentage of the total sale of elements of the final product j, which makes the enterprise sale in the subsequent steps t;
  - the time of delivery of the i-th copy of the j-type final product contracted in step t;
  - the margin at sale of the i-th copy of the j-type final product ordered in step t;
  - the number of delay rounds at delivery of the copy of the j-type final product ordered in the step t.

The characteristics of the strategy: As a result of the strategy choice, the change of values occurs of the decision attributes responsible for:

- Actions related to the purchase of the component; they comprise of modification of the number of preferred purchased components of certain types, transaction conditions depending on the number of components being bought, proposed and accepted prices and times of delivery
- Actions related to the sale of elements; they comprise of modification of the number of preferred final products sold, transaction conditions depending on the number of components being bought, proposed and accepted prices and times of delivery.
- Actions related to the conclusion of the long-term contract with the enterprise selling components and to conditions of such a contract comprising modification of the accepted price, the accepted number range of elements concerning the transaction and consequences of the contract break.
- Actions related to the conclusion of the long-term contract with the enterprise buying final products manufactured by the enterprise, comprising of modifications of the accepted price, the accepted number range of elements concerning the transaction and consequences of the contract break.

Evaluation of the results of strategy using in the given states. The evaluation of using a strategy (*Eval*) may be done in different ways. Currently we plan to apply machine learning technique, thus carrying out many simulations and evaluations of choice results of certain strategies by examining the goal function (*G*) values, after different, given numbers of simulation steps. The evaluation may be performed with the use of different criteria:

- The average gained assets in round t after the choice of the given strategy described either using cash only or considering values of purchased components;
- The maximal gained assets;
- The minimal gained assets;
- The probability of transfer to other simulation patterns and quality evaluation of these subsequent patterns by using the evaluation

4. Realisation

The system was realised with the use of the agent platform JADE. The scheme of the architecture of the system is presented in Fig. 3.

In the figure, the main types of interactions between agents are presented: the sending of initialisation information, exchange of data about offers and request realisation and synchronisation of steps.

The additional kinds of agents, necessary for the realisation of the simulation – *Data Agent* and *Simulation Agent* are presented. The Data Agent is responsible for storing data about the simulation configuration and providing them to the agents as well as for the gathering of data necessary for the visualisation, generation of statistics and rapports.

Simulation agents decide on transitions to subsequent simulation steps and phases and informs agents about it. Every simulation step consists of two phases: (i) negotiation and production phase and (ii) delivery and data actualisation phase. During the phase (i) negotiations, productions, ordering of buying components and realisation of requests are performed. During the phase (ii) an actualisation of data takes place, concerning prices of products by agents and the delivery of ordered components and products.

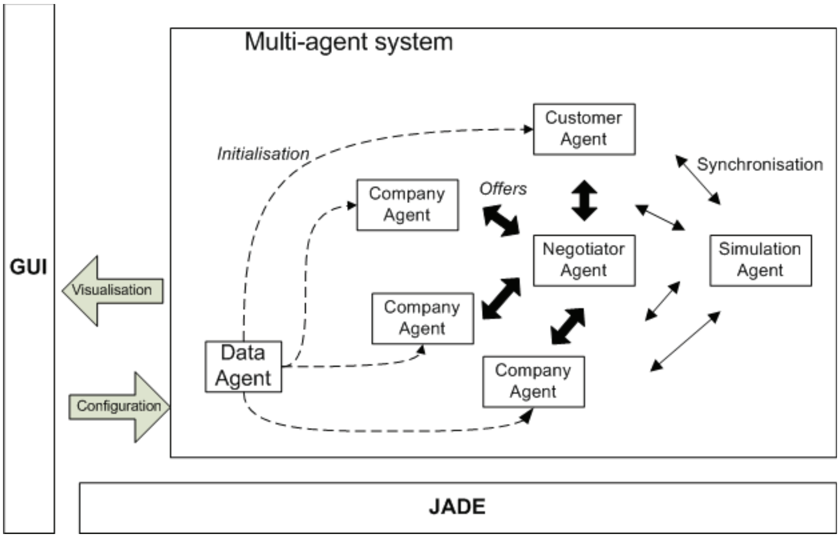

Figure 3: Scheme of the system architecture.

The defined model of behaviours of agents, makes it possible to implement activities which are executed by the agent parallelly. The given behaviours are triggered by the arrival of a message or a cyclic time event.

For identification of the situations using clustering techniques, the environment Weka [13, 14] was used.

5. Selected experiments

During the valuation of environment and its components, different experimental scenarios were performed for different market conditions, and especially, chosen sets of companies and their configurations and different characteristics of time distribution of demand for final products. Experiments concerning the accuracy of prediction offered by different kinds of standard predictors and by an adaptive predictor are described in the next subsection. In the following subsection, the results obtained using rule-based and clustering algorithms for decision making are presented.

5.1. Adaptive Predictor

Analysis of the adaptive predictor configuration. The aim of research was to fix the possibility to connect many different algorithms of demand prediction into one adaptive algorithm. It is known that each of them has its own specificity and behaves differently for different data. Merging them into one and applying the best one in the very moment should be advantageous. Adaptive predictor has originated by encapsulating algorithms: *Moving average*, *Arithmetic average*, *Holt*. Each of these algorithms is fed by the same data and in every simulation step we obtain the values predicted in such a way. The values are used subsequently to establish prediction quality and to choose the best algorithm at any moment. To fix the prediction quality we apply a simple measure which consists of summing up a prediction error of the last *n* steps. An absolute difference between the real and predicted demands is assumed as a prediction error.

Adaptive prediction is controlled by two parameters. The first one is a number of steps, after which, cyclically, the enumeration of quality of predictors and the choice of the best one (period of the choice of prediction - OP) is performed. The second parameter is a number of historical data (the formerly predicted values), which are used to fix the prediction quality (the value is denoted as H).

The research was done for the following runs of demand for final products: (A) – single parabola, (B) – double parabola (sinus), (C) – double parabola disturbed by a random variable [-2:2], (D) – constant increase disturbed by a random variable [-2:2], (E) – constant value disturbed by a random variable [-5:5]. The whole research of demand comprises 100 steps.

As the research has proved, an adaptive predictor gives the best estimation of the demand for each examined example. In the table below, the total results are presented. The single prediction algorithms are compared with the adaptive algorithms. The values mean percentage of the prediction error against the real demand.

Table 1: Prediction error [%]

Series	Moving average	Arithmetic	Holt	Adaptive
A	6.58	7.49	8.93	3.65
B	4.12	5.72	5.55	1.72
C	2.83	3.90	3.72	1.13
D	8.37	7.70	10.30	4.69
E	12.32	12.57	13.48	8.52

It is also necessary to check for which parameters OP and H, the adaptive algorithm gives the best results. The research has proved that the best results are for values OP = 1. It is in agreement with expectations, because a more frequent evaluation of a prediction error allows a quicker switching to the better algorithm. The choice of optimal value H is more troublesome and it turns out that it depends on the assumed value OP and a type of the real demand. For OP = 1 the best results are obtained always for H = 1. If we increase the OP value, the optimal value H is also moved and in most cases the best solutions are gained when it is equal to the value of parameter OP.

For greater values of OP and H (above 10) the dependency does not always occur, in such a case, the type of examined data has an influence on results. The dependency OP and H seems obvious if the quality of predictors is evaluated in each 10-th step; the best is to use it for *n* last results of predictions.

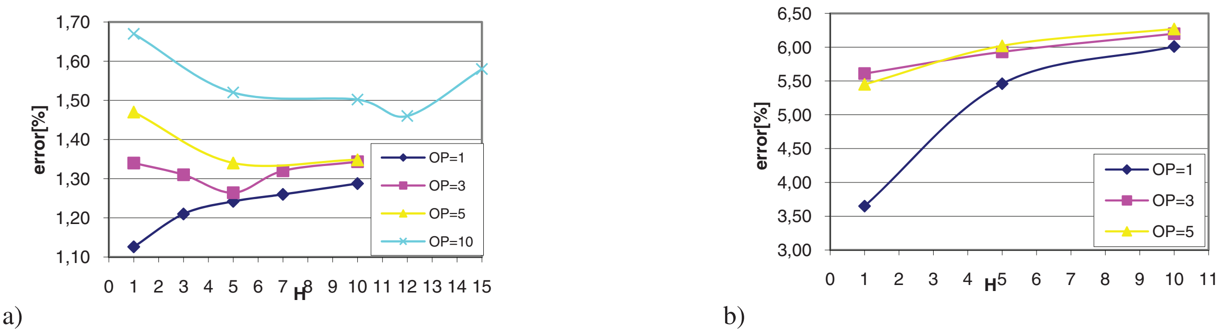

Figure 4: Value of the error demand for the final product as functions of OP and H for shapes of demand A) (Fig. a) and C (Fig. b)

Example of experiments with obtained configuration. After selecting the best configuration of the algorithm for a significant number of cases, the next goal to evaluate was, if the use of the more accurate prediction technique allows us to obtain a final better result expressed by the total incomes of companies and total level of stocks was applied.

Because of the different factors influencing the final results, the more accurate prediction did not lead to the better results in every cases. Especially, when unexpected increasement of the demand took place and the storage costs were relatively low, keeping higher level of stocks was more advantageous then having good overall demand prediction level.

Its strength was displayed especially for cases where demand had changing and complex characteristics and features of different prediction algorithms were necessary, the importance of predication accuracy also increased when high storage costs were used. We considered the final demand in the form of a step function with constant lengths of intervals, and two alternatively changing values. The total incomes obtained by companies using different prediction algorithms were as follows: adaptive: 265888151, Holtz: 224417881 (16 % worse than using the adaptive), moving average: 256302250 (4 % worse than using the adaptive), arithmetic: 257172944 (4 % worse than using the adaptive).

The adaptive algorithm quickly emerges after the real demand, which allows the warehouse to better adjust to the given situation.

5.2. Situation identification using rule-based algorithm and clustering techniques

Two solutions presented in sections 3.3 and 3.4 were compared: using empiric decision rules or by using clustering techniques for the identification of the situation.

The rules concerned decision about the setting of price margin for selling products, conditions offered for buying components and the level of the stocks.

For the identification of the situation in the performed tests we used simplified, in regard to the one described in section 3.4, set of measures describing the situation. For the analysis of the results and the construction of the clusters in the performed tests following data about company was taken into consideration: total capital increase, gross and net income increase, outcome increase, warehouse costs increase.

For the given product and producer the following data was considered: global demand increase, global market share of the producer for the given product, global gross income increase, margin increase, mean delivery time, part in global sale, price increase, used production capacity increase,

In subsequent steps decisions were evaluated according to income of gain obtained in the subsequent steps.

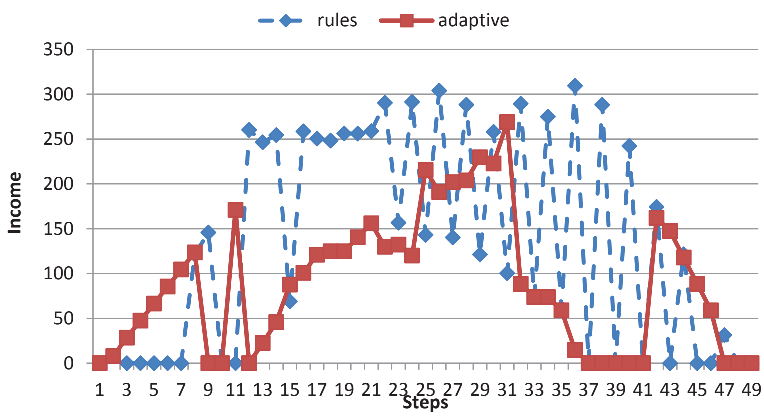

Figure 5: Gain of selected company for subsequent steps with the use of strategy selection by rules of by clustering

In Fig. 5 we can notice, that although the obtained results (total income) are slightly better for the rule–based cases, in the system using identification of the situation and adaptive strategy, the changes have a more subtle tendency, without large fluctuations.

6. Conclusion

Within the scope of this work, an environment for modelling and optimising strategies of market subjects was prepared. We especially presented a module playing strategical manager of the agent company, which has to make some general decisions about the choice of system strategies and which particularly decides on the best prediction technique for a given market situation and margin level. Two pilot versions of the strategical manager were used: one based on the set of rules, the second using the clustering technique for identifying the situation.

Subsequent work will concern the better choice and adjustment of measures used for identifying the situation in the clustering process. We are also going to extend the set of used strategies (and ways of configuration of actions) and test different methods of strategy evaluations for given situations.

Acknowledgements: This work was partially supported by the Polish Ministry of Science and Higher Education grant no. N N516 366236. The authors thank to students of Computer Science of AGH-UST who participated in the development of the modules of the environment, and especially P. Janisz, D. Gałysa, K. Dziedzic, J. Herzyk, W. Adamek, M. Grudzień, M. Tkacz, G. Gunia and A. Magura–Witkowska.

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